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Published in:
13th International Conference on Urban Drainage (ICUD 2014)

Publication date:
2014

Document Version
Publisher's PDF, also known as Version of record

[Link back to DTU Orbit](#)

Citation (APA):
Åström, H. L. A., Sunyer Pinya, M. A., Madsen, H., Friis Hansen, P., Rosbjerg, D., & Arnbjerg-Nielsen, K. (2014). Describing concurrent flood hazards in a risk assessment decision framework using a bayesian network methodology. In *13th International Conference on Urban Drainage (ICUD 2014): Abstract Book* IWA Publishing.

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Describing Concurrent Flood Hazards in a Risk Assessment Decision Framework Using a Bayesian Network Methodology

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ABSTRACT

In this study we outline a risk-based decision-making framework for flood management purposes using a Bayesian network methodology. Flood risk assessments are often based on single hazard events. We acknowledge that with a changing climate, flood risk assessments need to be extended to consider several hazards and their possible simultaneous occurrence. Further, we argue that there is a need to include additional drivers of extreme events into a risk assessment in order to obtain a robust description of the occurrence of these events. It is widely accepted that large-scale weather systems influence local climate, and this addition to a risk assessment can ensure a more complete description of different flood inducing events. In our case study we focused on describing how our Bayesian method can assess the probability of concurrent events. We analysed high sea water level and precipitation events and used different threshold combinations of these hazards to assess the daily probability of concurrent events in Aarhus—the second largest city in Denmark. The results were validated through comparison of observed concurrent events in Aarhus. We showed that there was a clear variation in seasonal probabilities of concurrent events and distinguish weather systems with high probability of concurrent events.

KEYWORDS

Bayesian influence diagram, Lamb weather classification, flood risk assessment

INTRODUCTION

Urban areas are prone to flooding and can experience significant consequences due to a large amount of valuable assets. Several hazards may contribute to urban flooding; 1) extreme precipitation, 2) high sea water levels (sea surges), 3) extreme river discharges, and 4) high groundwater tables, or 5) a combination of these. In Denmark pluvial flood events have caused large damage in urban areas in recent decades. At the same time large projected increase in magnitude and frequency of extreme precipitation events have been assessed (Arnbjerg-Nielsen, 2012). This has led to more focus on extreme precipitation in flood management. In Denmark, largest cities are located at the sea coast. With anticipated sea level rise and possible increase in storm surge occurrence, we may also experience flooding due to extreme sea surges in the future. Additionally, concurrent extreme precipitation and sea surges may result in new challenges for urban drainage systems in coastal areas, as high water levels reduce the runoff capacity from heavy rainstorms. Flood risk analyses mainly focus on single hazard risks. This practice has been appropriate due to a low probability of concurrent hazards (Pedersen et al., 2012). A new challenge in flood risk management is to assess the risk of events that have not yet occurred but may, in the future, lead to tremendous damage to society. Concurrent hazards may be such events.

It has been recognized in previous studies (Pattison & Lane, 2012) that large scale atmospheric circulation, i.e. weather systems, can be a useful tool to link extreme events with its generating process and, hence, contribute to an improved understanding on how and when extreme events may occur (Garavaglia, et al., 2010). Åström et al. (2013b) linked high sea water level events and precipitation events with weather patterns and could identify weather patterns that have a significantly higher occurrence of extreme events in Denmark. The study used Lamb weather classification to describe large scale weather systems. Hence, we include weather system classification to our risk assessment to provide a more robust description of extreme event occurrence.

This study developed a Bayesian Influence Diagram (ID) for risk-based decision-making purposes in flood management. We show how the method includes several hazards in the assessment and provides a flexible way to assess the benefits of different adaptation measures. In our case study we focus solely on describing how our method includes several hazards and how the probability of concurrent events is assessed in the method. We validate the results using observed data of concurrent events. As a case study area we use Aarhus, the second largest city in Denmark.

METHODOLOGY

Lamb weather type classification

The Lamb weather type classification is based on synoptic pressure and flow direction and, hence, it describes the prevailing pressure characteristic and indicates the presence of storms (Jenkinson & Collinson, 1977; Jones, et al., 1993). The computation of Lamb weather types is based on daily mean sea level pressure (MSLP) data from 16 grid points around Denmark, shown in Figure 1 (left). For a detailed description of the calculation of the weather types in Denmark we refer to Åström et al. (2013b). Åström et al. (2013b) developed a daily Lamb weather type catalogue in Denmark for the time period 1979-2001 to evaluate which weather types generate high precipitation and sea surges.

Table 1. Lamb weather classes used in the risk assessment

Classes	Symbol
Anti-cyclonic	A
Cyclonic	C
Northeasterly	NE
Easterly	E
Southeasterly	SE
Southerly	S
Southwesterly	SW
Westerly	W
Northwesterly	NW
Northerly	N

The Lamb classification has 26+1 classes subdivided into 8 directional types (N, NE, E, SE, S, SW, W, NW), 2 non-directional types (cyclonic C and anti-cyclonic A), 15 combined complex hybrid types (CN, CNE, CE, CSE, CSW, CW, CNW, AN, ANE, AE, ASE, AS, ASW, AW, ANW), and additionally one unclassified type (U) (Jenkinson & Collinson, 1977). We followed the approach adopted by Trigo et al (2000) and combined the Lamb types into 10 weather classes. This was shown by Åström et al. (2013b) to provide an equally

good assessment of flood generating weather systems and by doing so we aimed to devise a more reliable statistical analysis of the restricted amount of available data. The classes used in our study are shown in Table 1. Each hybrid type was included with a weight of 0.5 in the corresponding directional and cyclonic/anti-cyclonic class (i.e. CN was included by 0.5 to class C and 0.5 to class N). The seasonal and annual probabilities of Lamb weather classes in Denmark for time period 1979-2001 is presented in Figure 1 (right) (Åström et al., 2013b). Dominating weather classes over Denmark are A, C and W which count for 57 % of all days.

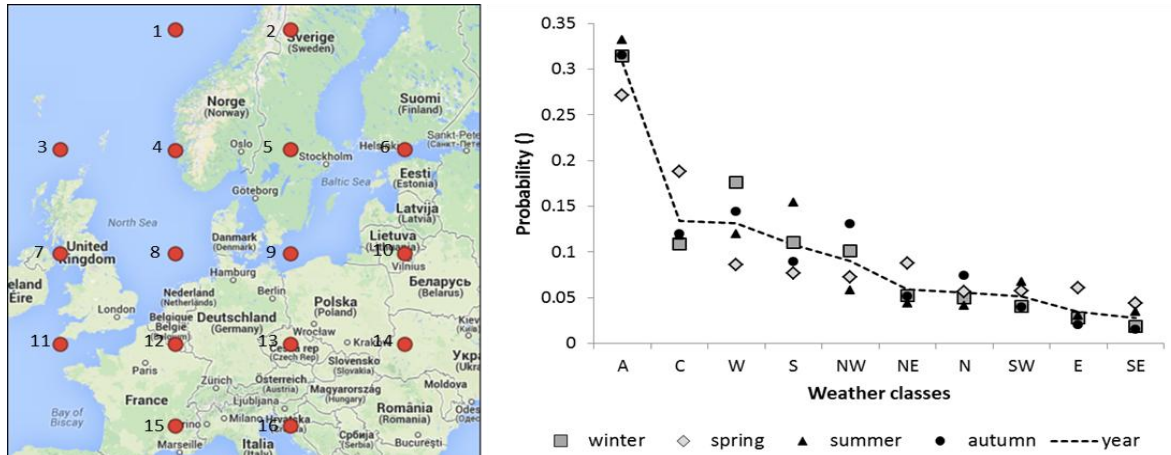


Figure 1. Left: 16 grid points used to calculate Lamb weather types over Denmark, right: calculated seasonal probabilities of Lamb weather classes in time period 1979-2001

Bayesian Networks and Influence diagrams

Bayesian networks (BNs) are based on Bayes' theorem developed in the 18th Century, which expresses the relationship between probabilities $P(A)$ and $P(B)$ and the conditional probabilities $P(B|A)$ and $P(A|B)$ of two variables A and B (Charniak, 1991). With a Bayesian interpretation of the theorem, the posterior distribution $P(A|B)$ is computed as the product of the prior distribution $P(A)$ and a term accounting for evidence, the so-called likelihood function $P(B|A)$ (Charniak, 1991).

The construction of a BN starts with defining a graphical depiction of the causal dependencies between variables within the system being studied. Variables in the system are presented as elliptical nodes, called chance nodes. The dependencies between the nodes are presented as arrows, and the direction of the arrow defines the dependency (Borsuk, et al., 2004). Nodes with no incoming links are called root nodes, and nodes with no outgoing links are called leaf nodes. Every node with outgoing links is called a parent node to the node receiving the link, which is a child node. In risk assessments the system at risk can be complex, and the graphical representation is, therefore, an effective means to communicate the system at risk for involved stakeholders, decision-makers and experts and encourages to a critical discussion of the system configuration (Åström, et al., 2013a). This ensures a mutual agreement and understanding of the system structure presented in the BN.

Once the system configuration has been agreed on, input data are added to each node. Input data to BNs are added as so called Conditional Probability Tables (CPTs) in which the domain of all possible states taken by that node is listed together with probabilities of these states conditional to the parent nodes (Borsuk, et al., 2004). Root nodes are assigned unconditional distributions. Input data to CPTs can be gathered from numerous sources; from expert opinions and statistical data analyses, and from various research fields. This makes BNs highly suitable for multi-disciplinary studies such as flood risk management (Carriger &

Newman, 2011, Åström, et al., 2013a). When CPTs are set in the system, the posterior probability distributions are compiled using the Bayesian theorem according to the so-called chain-rule. Once the network is compiled, Bayesian inference can be performed, i.e. the posterior probabilities of the nodes in the network are computed when values of other nodes are observed and entered as evidence. When new evidence is entered the posterior probabilities are updated (Charniak, 1991). A BN provides automatically a description of the uncertainty in the system, since each variable is defined as a probability distribution.

If the network only contains variables related to the system process, it is known as a Bayesian Network (BN). A Bayesian Influence Diagram (ID) is a BN that also contains nodes with actual decisions (decision nodes) and the costs and benefits (utility nodes) of those decisions. An ID does not only model the system process but also how decisions affect those processes and how the expected change affects the loss or payoff (Carriger & Newman, 2011). Hence, an ID as a decision-making tool can adapt to change, re-assess the process when new evidence is gathered, and estimate the costs and benefits necessary for decision-making within flood risk management.

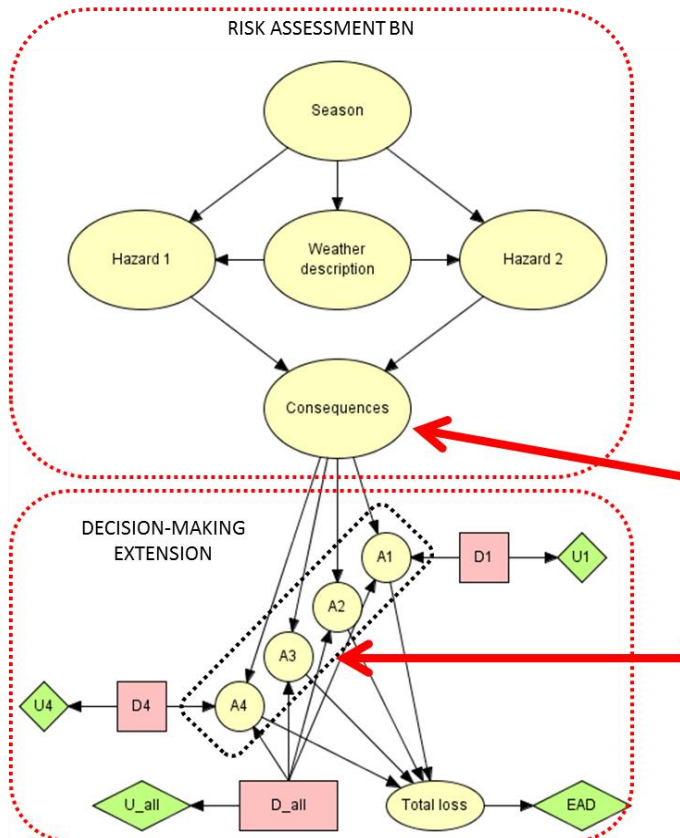
An Influence diagram for decision-making in flood risk management

In this study we constructed a risk assessment and decision-making framework including several hazards using an ID. The network is presented in Figure 2a. This ID is divided into two parts 1) Risk assessment BN and 2) Decision-making extension. The “risk assessment BN”-part consists of 5 chance nodes. Two hazard-nodes are included (“Hazard1” and “Hazard2”) and these hazards are conditionally dependent on “Weather description”- and “Season”-nodes. Hence, we assume that the weather system description and season provides sufficient information to assess the probability of hazard extremes. The leaf node of the BN, i.e. “Consequences”-node, describes the overall flood consequences in the area and is dependent on the joint probabilities of all included hazards. Consequences are in this node described as flooded area (ha). To obtain consequence estimations, 1D-2D flood simulations are run, and the flooded area is assessed for single hazards and simultaneous hazards. The risk assessment BN enhances an understanding of the overall probability of flooding in an area, but to contribute to flexible decision-making the network should allow for testing benefits of different adaptation options and describe the risk and change in risk due to adaptation measures as monetary values.

A “decision-making extension”-part was combined with the risk assessment BN. In this extension the studied urban area is divided into sub-regions (A_1, A_2, \dots, A_n) represented in Figure 2a as small, round chance nodes. The division of the urban area is exemplified in the figure as the flood simulation divided into four sub-regions. These sub-networks in the ID, i.e. additional built-in BNs, provide impact assessments for each sub-region in the urban area accounting for a number of consequence classes (flooded houses, roads, railways etc.). Such a division of the entire area enables local impact assessments, which in turn allows testing of both local adaptation measure and adaptation measures what affects the entire urban area. Adaptation measures were added to the network as decision nodes (red, rectangular). In the illustrative network in Figure 2a local adaptation measures are tested on sub-regions A_1 and A_4 through sub-region-specific decision nodes D_1 and D_4 . Further, adaptation measures that affect the entire urban area are represented by the decision node “D_all”. To each decision node a utility node (diamond shaped, green) was added to describe the cost of different adaptation options.

In the “Total loss”-node the impact assessments of all sub-regions are combined into one overall impact assessment of the entire urban area. This node describes with a probability density function (pdf) the monetary loss for the urban area. With a utility node the Expected Annual Damage (EAD) is finally assessed for the urban area. When testing different adaptation options, the total loss, EAD, and cost of the adaptation option (U_n -nodes) change accordingly and provide information about the overall risk and benefits from adaptation. With the described ID the decision-makers can therefore find the best combination of adaptation measures for the urban area, which is a combination of sub-regional adaptation measures and adaptation measures that affect the entire urban area.

2a)



2b) CASE STUDY

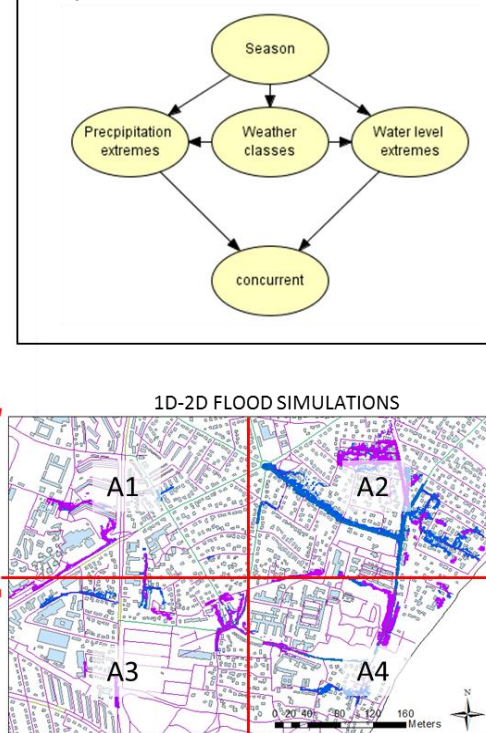


Figure 2. Layout of the Bayesian Influence diagram for decision-making based on a risk assessment of several hazards

CASE STUDY DESCRIPTION

In our case study we exemplify how the probability of concurrent event is assessed in our decision-making framework based on a risk assessment BN. We use Aarhus, the second largest city in Denmark as our case study area. We had access to precipitation data by The Water Pollution Committee of The Society of Danish Engineers (Spildevandskomiteen, SVK) for time period 1979-2001. Water level data were provided by the Danish Meteorological Institute (DMI). With regards to Lamb weather circulation, daily weather types over Denmark assessed by Åström et al. (2013b) were used. ERA-40 re-analysis meteorological data produced by European Center for Medium-Range Weather Forecasts (ECMWF) (Betts & Beljaars, 2003) were used in the calculations of Lamb weather types. Our case study BN is shown in Figure 2b.

Data input to the Bayesian Network

Seasonal probability distributions of weather classes were added to the CPT for the “Weather class”-node as presented in Figure 1(right). The states of precipitation and water level nodes were defined with threshold intervals of magnitude 0.1 m for water level and 2 mm/3h for precipitation, and data were fitted to exponential distributions. Daily probability density functions (pdfs) were based on daily maximum events in order to ensure that the analyzed events were independent from each other. In Figure 3 the analyzed events are divided over the different threshold intervals. Figure 4 present annual cumulative probability distributions of sea water level and precipitation events in each weather class. Weather classes W, SW, and NW have high probabilities of both precipitation and water level events in Aarhus.

To assess the probability of concurrent events, we included a Boolean type “concurrent”-node (in Figure 2b), which describes the daily probability of obtaining a concurrent event. We assessed the daily probability of concurrent events for different combinations of water level and precipitation thresholds and compared the results with observed concurrent events for time period 1979-2001 in Aarhus. Events were counted as concurrent if they occurred during the same day.

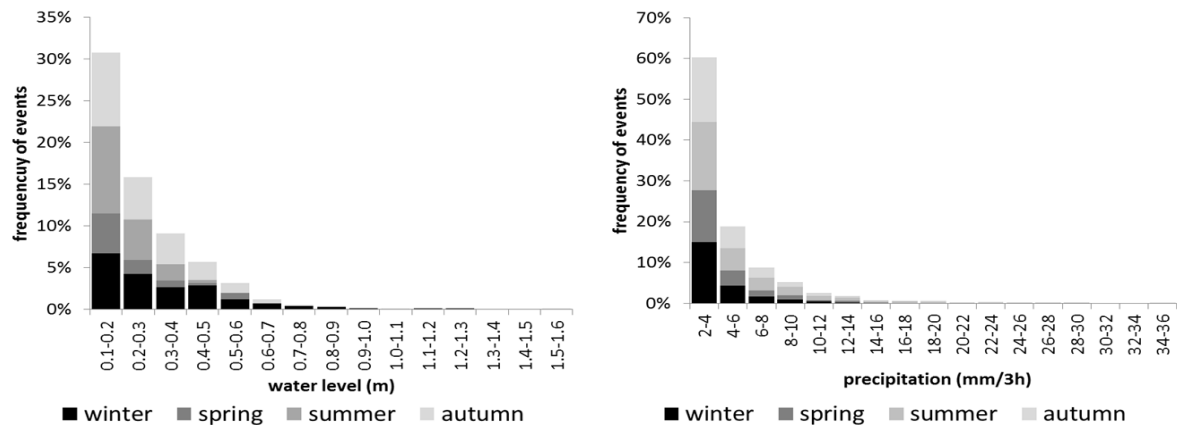


Figure 3. Frequency of high sea water level (left) and precipitation (right) events in different threshold intervals for the time period 1979-2001 for each season

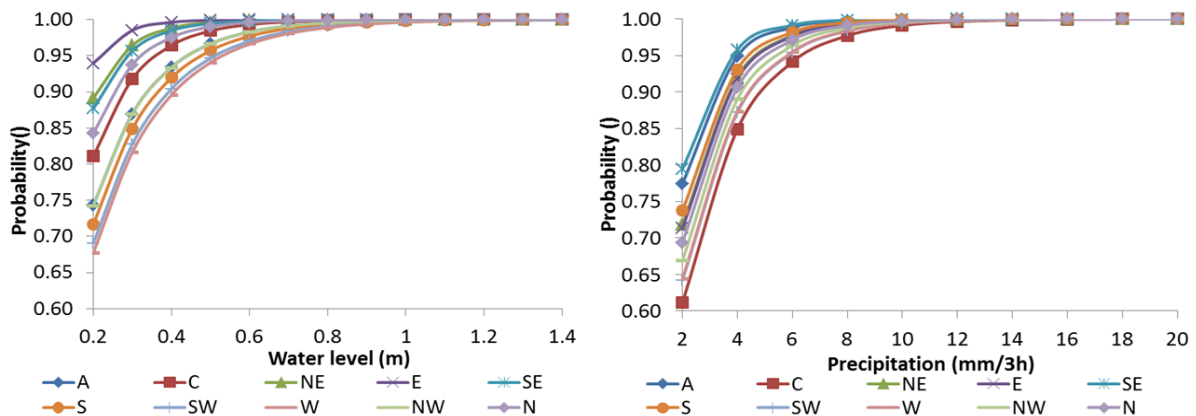


Figure 4. Cumulative probability distributions of high water level (left) and precipitation (right) events in each weather class

RESULTS

Figure 5 presents seasonal cumulative probability distributions for water level and precipitation events obtained from the BN. Both hazards have a high probability in autumn. In Figure 6 observed and assessed (from the BN) daily probabilities of concurrent events (multiplied with 10^4) using combinations of different precipitation and water level thresholds

are shown. We used thresholds 2, 4, 6, and 8 mm/3h for precipitation and 0.3, 0.4, 0.5, and 0.6 m for water level. With low precipitation threshold (2mm/3h) the number of concurrent events is significantly overestimated in the BN. With higher water level and precipitation thresholds the observed and estimated probabilities of concurrent events have similar magnitudes. Figure 7 exemplifies the variations in seasonal probabilities of concurrent events and probabilities of concurrent events for the different weather classes using thresholds 0.4 meter and 4mm/3h, which corresponds approximately to 20 water level and precipitation events per year. The line represents the annual daily probability of concurrent events (i.e. 0.0043). Autumn has a significantly higher probability than the other seasons. Further, we found a large variation in the probability of concurrent events for the different weather classes. Classes SW, W, and NW all have a higher probability than the average annual.

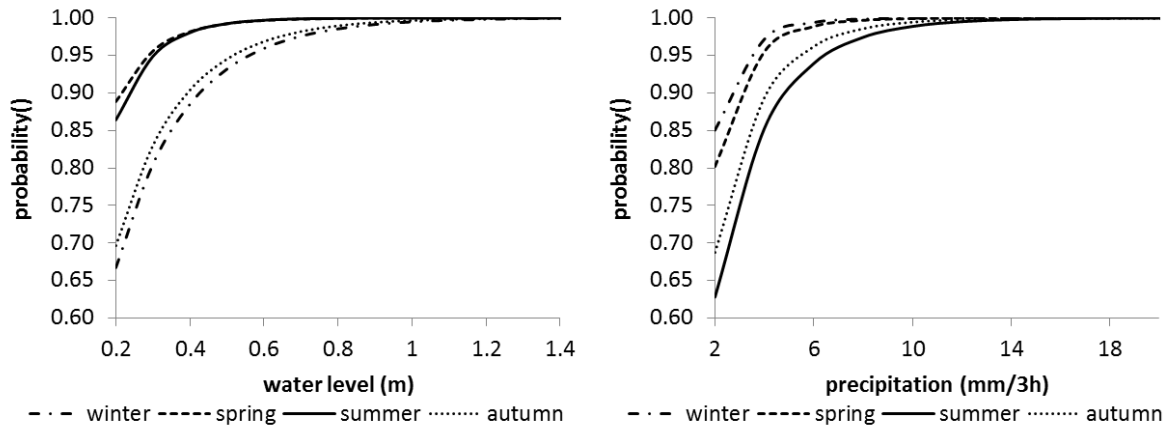


Figure 5. Seasonal cumulative probability distributions of high water levels (left) and precipitation events (right)

OBSERVED					BAYESIAN NETWORK						
precipitation (mm/3h)	water level (meter)				precipitation (mm/3h)	water level (meter)					
	0.3	0.4	0.5	0.6		0.3	0.4	0.5	0.6		
	2	77	43	25		11	2	287	101	80	45
	4	44	26	18		8	4	83	43	23	13
	6	27	14	10		5	6	28	14	8	4
	8	15	10	5		1	8	10	5	3	1

Figure 6. Observed daily probability of concurrent events (left) and daily probabilities of concurrent events obtained from the BN (multiplied with 10^4)

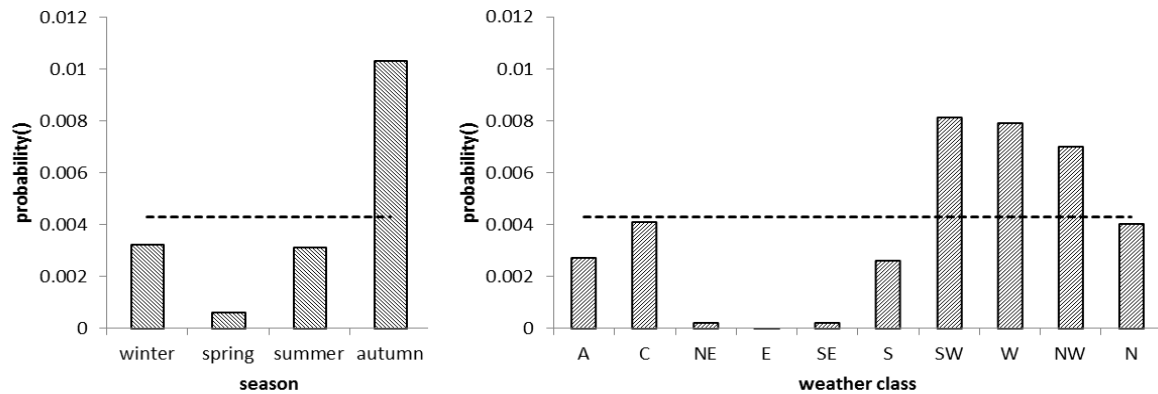


Figure 7. Probability of concurrent events in each season (left) and weather class (right) with thresholds 0.4 m (water level) and 4mm/3h (precipitation)

CONCLUSION

In this study we presented an ID for flood management decision-making, which can assess flood risk in sub-regions and the total risk in an urban area. This enables flexible testing of different adaptation measures in the system. With a graphical description an ID improves the understanding of the system and boosts the decision-making capacity. With probability distributions IDs also ensure a robust assessment of the uncertainty in the decision-process.

We assessed the probability of concurrent events as described in our decision-making framework and found that with low thresholds our method significantly overestimates the number of concurrent events. This deviation is from a risk assessment perspective negligible. Very low precipitation thresholds do not result in negative impacts in an area and, hence, do not affect the total risk. For higher thresholds, our method provided probabilities of similar magnitude as was observed. We found that autumn has a larger than average probability of concurrent events, which is in accordance of what we expected based on the pdfs of precipitation and water level events. Further, we found that there is a clear variation in the probability of concurrent hazards in the different weather classes. Westerly weather direction (W, SW, and NW) showed a higher than average annual probability. Again, this was as expected since these weather classes showed high probability of both water level and precipitation events in Aarhus.

ACKNOWLEDGEMENTS

This work was carried out with the support of the Danish Council for Strategic Research as a part of the project RiskChange, contract no. 10-093894.

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